CAAP Quarterly Report

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Project Title: Improved NDT Detection and Probabilistic Failure Prediction for Interacting Pipeline Anomalies

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Business and Activity Section

(a) Contract Activity

No modifications were made to the contract.

(b) Status Update of Past Quarter Activities

Aim 1: We have coded new python scripts to generate databases of ultrasonic finite element simulations (FEA) of a three-dimensional plate geometry with embedded cracks of varying characteristics. Two databases have been created, with size and location as variables for each one. Ultrasound crack detection validation experiments were conducted. Training of two neural networks was performed in PyTorch and validated with experimental signal. Good accuracy was achieved for both size and location prediction. We have also started to develop steps that will be taken to extend our newly developed fundamental foundations to detect interacting anomalies considering crack with corrosion wall loss and crack in presence of another crack. We have also written a manuscript and submitted to a peer-reviewed journal for publication. This manuscript is titled “Finite element simulations and neural network based accurate crack size and location prediction for non-destructive ultrasounds.”

Aim 2: We have conducted literature study on GTN modeling for different grades of API 5L carbon steel and found calibrated parameters as well as experimental results for our research. As a preliminary learning exercise, we also calibrated the GTN model for 316L steel which is typically used in LNG flexible pipes. We have performed FEA to validate GTN parameters for certain scenarios. We have been conducting literature review on Bayesian statistics for improved probabilistic failure predictions.

Cost share activity

Partial support for graduate student tuition was provided by Brown University School of Engineering as per the cost share agreement.

1. Background and Objectives in the 5th Quarter

1.1 Background

According to the American Iron and Steel Institute (AISI), steel can be broadly categorized into four groups based on their chemical compositions: Carbon Steel, Alloy Steel, Stainless Steel and Tool Steel. Carbon steel pipes have the largest market share, as they can be used for many high and low-temperature applications. There are different specifications of carbon steels (such as A53, A333, A106, and API 5L). We have chosen API 5L because it is commonly used for line pipes used in oil and gas applications. The steel materials are also graded based on their mechanical properties. Most common grades of API 5L are API 5L GRB, X42, X52, X56, X60, X65, X70 and X80. Through literature study, we have identified the GTN parameters for the following materials. X60 carbon steel parameters were calibrated against experiment data in [1]; X65 carbon steel parameters were calibrated against experiment data in [2]; X70 carbon steel parameters were reported in [3]; X80 and X100 carbon steel parameters were calibrated against experiment data in [4]; a separate calibration for X65, X80 and X100 steel are calibrated in [5]. No record of calibrated GTN parameters for X52 steel were found, but experimental stress strain data with initiation of failure were found in [6]. Manual calibration can be accomplished by extracting the data from the article.

The goal for all statistical inference is to determine the probability of the hypothesis given the data obtained. In addition to developing probabilistic failure methodology, we are additionally studying the role of Bayesian methods for pipeline failure predictions as unlike the conventionally used frequency based inference, Bayesian inference does not stop at simply validating a hypothesis. Using data along with our probabilistic pre-data hypothesis, Bayesian inference allows us to calculate a post-data hypothesis.

1.2 Objectives in the 5th Quarter

Aim 1: During the last quarter, we have started to study the computationally and numerically challenging 3D embedded crack geometry (vs useful and computationally practical 2D cases). Our objectives in this quarter are: (1) create 3D ultrasonic finite element simulation capabilities and start preparing signal databases for single crack parameter predictions, (2) transition the neural network platform from MATLAB to PyTorch for increased versatility and capabilities, and (3) to conduct preliminary ultrasound NDT validation experiments.

Aim 2: During the last quarter, we have conducted early failure analysis for a notched plate with ABAQUS embedded GTN model. Our objectives in this quarter are: (1) identify material data available in literature (which is included in 1.1, the background section), and (2) conduct additional GTN parameter calibration by comparing our finite element simulation against experiment data found in the literature.

2. Experimental and Computational Program in the 5th Quarter

2.1 Experiments

Olympus EPOCH 650 Digital Ultrasonic Flaw Detector was used to create ultrasonic signal. **Figure 1** shows the 3D metal printed embedded crack steel test samples. Test sample #1 (mentioned in the previous quarterly report) was picked for validation experimental purposes. **Figure 2** shows the received ultrasonic signal on the unit display and extracted digital data.

Figure 1. 3D metal printed test samples with embedded cracks

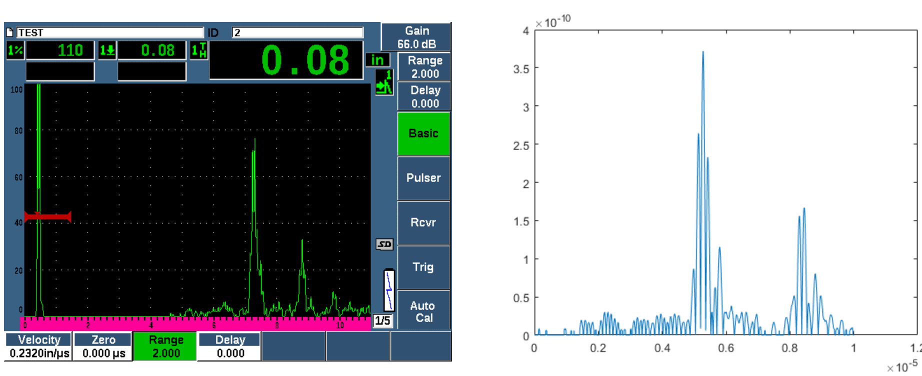

Figure 2. Left: Screenshot of experimental signal of testing sample #1 on EPOCH 650; right: acquired digital signal output from the unit (initial pulse removed)

2.2 Computational work

All computations were conducted on workstation. All our numerical study used an ultrasound wave of 5 MHz frequency, in accordance with EPOCH 650 unit and wavelength of ~1.2 mm, the numerically stability requirement we obtained that 10-15 meshes per wavelength provides a stable practical element size.

A 3D steel flat pipe section geometry with length and width both being 40 mm and thickness 19 mm (~3/4 inch) was used in our new simulations. A 5 MHz raised-cosine type waveform was applied as boundary condition to the top surface of the simulated pipe. Profile for this waveform is shown in **Figure 3**. Step size is fixed at $2 \times 10^{-9}\ s$ which corresponds to a 500 MHz sampling rate. Anomalies in the form of embedded penny-shaped cracks are placed in the middle of the plate. We conducted dynamic numerical simulations in Abaqus/Explicit. Displacement histories of a line of nodes are averaged to create the received signal.

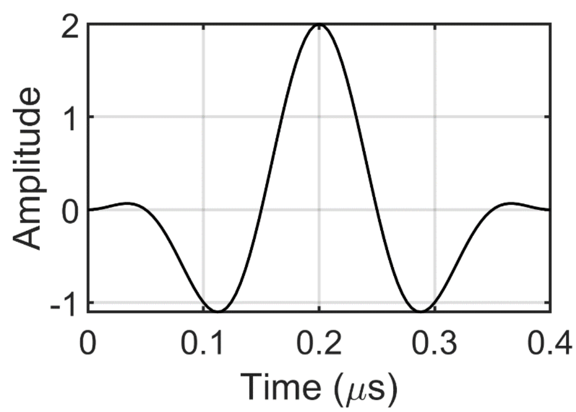

Figure 3. 5MHz, 2 period raised-cosine type pulse signal used in the simulations

3. Results and discussion

3.1 Technical approach and results: Aim 1

Four crack parameters are identified: crack long axis (or size) $\boldsymbol{a}$, crack short axis $\boldsymbol{b}$, crack location in terms of the depth $\boldsymbol{d}$, and the crack orientation $\boldsymbol{\theta}$**.** Since the short axis is not as important as the other three parameters in terms of a structure's failure behavior, we fix b = 0.6 mm for all simulations.

Based on the parameters of test sample #1, we have purposely created 2 databases, one of which has the same size but varying location and the other same location but varying size. The information of the databases is summarized in **Table 1**. The goal of these two databases is for single crack parameter prediction which can be validated by sample #1.

Table 1. Summarize of databases and sample #1 with different parameters, bold numbers indicate a range in which the corresponding parameter varies

	a (mm)	b (mm)	y (mm)	θ	Number of simulations
Sample #1 (experimental)	4	0.6	12	0	NA
Database 1	**[1, 5]**	0.6	12	0	235
Database 2	4	0.6	**[7, 15]**	0	226

Starting this quarter, we have been transitioning our neural network platform from MATLAB to PyTorch. Raw data formatting, wavelet packet transformation (WPT) and feature extraction are still performed in MATLAB, but the architecture of neural network as well as training and testing are performed using PyTorch. For these two databases, a three-layered neural network is utilized with 100 neurons in the hidden layer. Backpropagation with gradient descent algorithm is used to minimize loss function. The training of neural network is stopped once epoch exceeds 100000.

In order to demonstrate the prediction capability with better visualization, for both databases the training data is 90% of the whole database and the rest 10% are treated as test data for which the following figures are plotted. In **Figure 3**, the testing data are plotted respectively for two neural networks trained with varying crack size and crack location. For both cases, the testing data are clustered near the black dashed line which represents perfect prediction. Size prediction is slightly better as almost all the data points line on the black line.

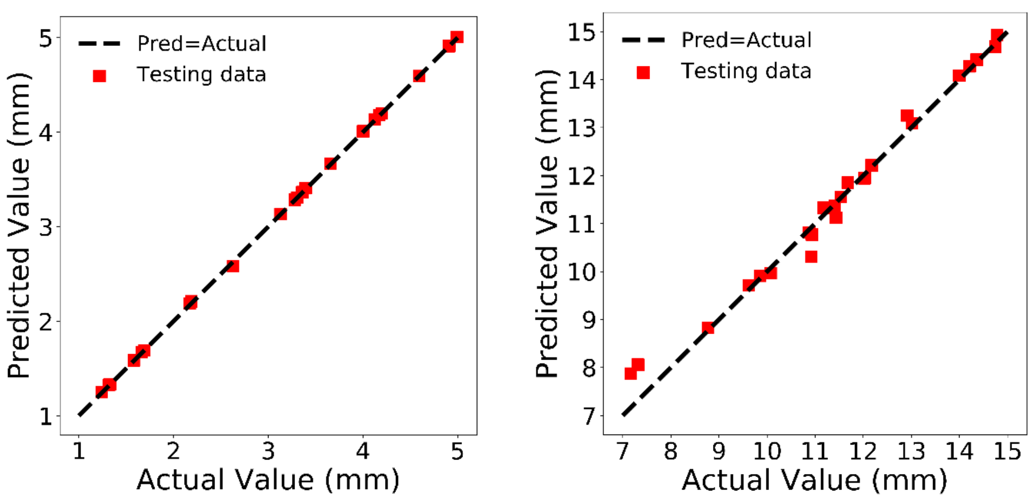

Figure 3. Neural network performance on predicting **crack size** (left) and **crack location/depth** (right) for testing data. Black dashed line represents where perfect predictions should lie on.

We then evaluate the performance more rigorously using statistical properties. Mean absolute percentage error (MAPE) is defined as

$$\boldsymbol{MAPE} = \frac{\mathbf{1}}{\boldsymbol{N}}\sum_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{N}}\left|\frac{\boldsymbol{p_i}-\boldsymbol{t_i}}{\boldsymbol{t_i}}\right|$$

where $\boldsymbol{p_i}$ is the i-th predicted value and $\boldsymbol{t_i}$ is the i-th target (actual) value. $\boldsymbol{R^2}$ is the coefficient of determination that characterizes the degree of fitness. The performances of both neural networks are given in **Table 2 and 3**. For crack size prediction, MAPE is below 1% indicating highly accurate prediction. The trained neural network predicts a crack size of 3.93 mm for a testing sample of 4 mm, which has an error of only 1.7%. This validates our early research hypothesis that a simulation trained neural network is capable of handling experimental/real life data. *It is also the first reported validation experiment for a neural network that is trained with a three-dimensional crack database.* For crack depth prediction, MAPE is 1.91% which is higher than crack size. The trained neural network predicts a crack depth of 12.59 mm for a testing sample of 12 mm, which has an error 4.91%.

Table 2. Performance of trained neural network on testing data (simulation) and on experiment data for **crack size prediction**

Testing data	MAPE (%)	R^2 (%)	
	0.36	99.99	
Experiment data	Actual size (mm)	Predicted size (mm)	Relative error (%)
	4	3.93	1.7

Table 3. Performance of trained neural network on testing data (simulation) and on experiment data for **crack location prediction**

Testing data	MAPE (%)	R^2 (%)	
	1.91	99.11	
Experiment data	Actual depth (mm)	Predicted depth (mm)	Relative error (%)
	12	12.59	4.91

3.2 Discussion: Aim 1

In this quarter, we have accomplished the objectives listed for aim 1. Three dimensional databases were created and used for training neural network. Especially, we have fundamentally demonstrated that a simulation-driven neural network is capable of accurate prediction of crack parameters for experimental data. This is because our finite element simulation is correctly capturing all the physical phenomena of ultrasonic propagation and our feature extraction technique can preserve this information while reducing the input parameter space. However a major drawback is the time demand for creating a large database for 3D computational geometry. Since for multi-parameter prediction a much larger database is required, we need to ***further reduce the simulation time*** either by optimization of current methods or ***by introducing new fundamentals of within machine learning framework to relax the need for a large number of simulation requirements***. This methodology currently does not exist and if achieved will be a fundamental important contribution that can be applied to a broad set of problems.

3.3 Technical approach and result: Aim 2

Tensile experiments on a round notched bar made of API 5L X65 grade steel are reported in [2]. Engineering stress against engineering strain is given until the complete failure of the bar. In the same literature, the GTN parameters are also calibrated against the experiments, and given below in **Table 4**.

Table 4. Calibrated GTN parameters for X65 steel

Porous material parameters			
$\boldsymbol{q_1}$	1.5	$\boldsymbol{q_2}$	1
$\boldsymbol{q_3}$	2.25		
Void nucleation parameters			
$\boldsymbol{e_N}$	0.3	$\boldsymbol{s_N}$	0.1
$\boldsymbol{f_N}$	0.0008	$\boldsymbol{f_0}$	0.000125
Porous failure criteria			
$\boldsymbol{f_c}$	0.015	$\boldsymbol{f_F}$	0.25

Following the experimental setup in [2], we use Abaqus and an inbuilt GTN model to conduct finite element simulation for a notched bar under tensile testing, and the results are plotted against experiment data in **Figure 5**. The simulation results matched well with the experiment data, showing that we have successfully been able to utilize GTN model for further application. The stress strain curves between GTN model and experiment are not exact after the onset of failure but have very similar trends. Moreover, we conducted a simulation for the same geometry with no fracture behavior (marked 'Elasto-plastic' in the figure. The result is exactly the same as GTN model until the onset of fracture, demonstrating capability of GTN to capture fracture physics within material.

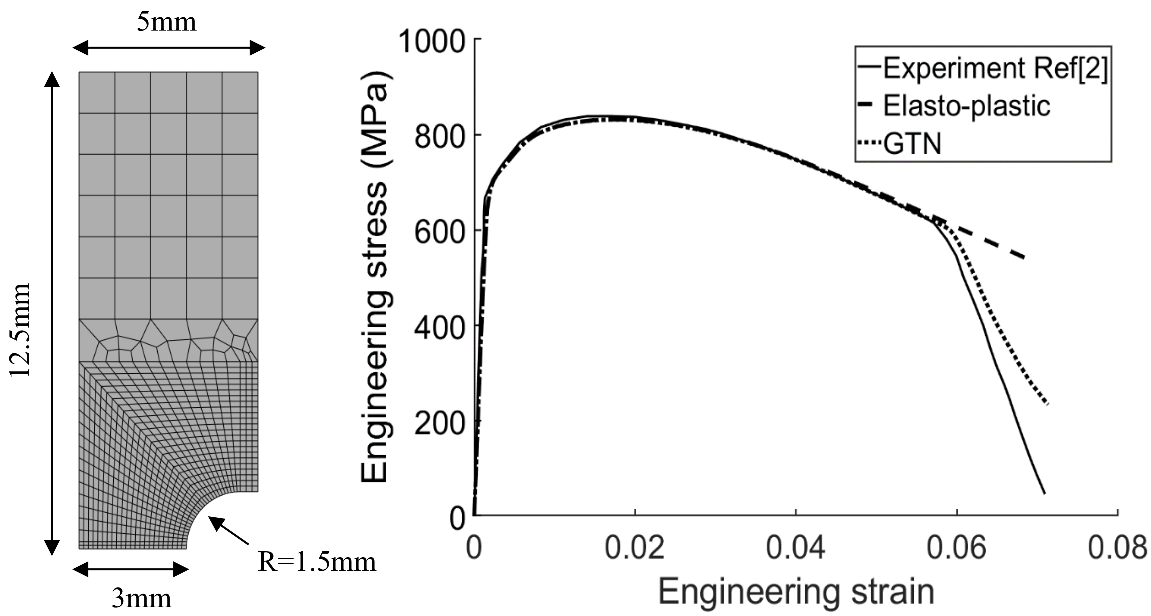

Figure 5. Axisymmetric view of the notched bar with mesh (left) and simulation results with experiment data for the bar under tensile testing (right).

3.4 Discussion: Aim 2

We have demonstrated that our GTN model finite element simulation set-up gave results that reasonably agree with the experiment data using calibrated parameters. The time of onset of fracture can be predicted in the model as well as the mechanical behavior after it. This validation will enable us taking further steps into modeling pipeline with flaws and their bursting pressure/failure as a function of flaw parameters.

The probabilistic framework essentially creates many different failure occurrences within a reasonable range dictated by the pipe failure model and creates a probability distribution from them. Using Bayesian inference that we are studying, it is possible to leverage real-world pipe failure data to make our model more precise. Bayes' law (see equation below) allows us to find the probability distribution of a hypothesis (such as burst pressure) from a set of data using a combination of statistics and our pre-data beliefs about this hypothesis.

$$\boldsymbol{P(hypothesis \mid data)} = \frac{\boldsymbol{P(data \mid hypothesis) * P(hypothesis)}}{\boldsymbol{P(data)}}$$

In the pipe failure model case, our pre-data beliefs would be the probability distribution outputted by the probabilistic framework. Given more and more data, Bayesian inference can be used to make the probability distribution of a parameter more precise. As the amount of data grows there are fewer possible parameters which can produce it. Hence, we can narrow the uncertainty on a parameter using data. Using real pipe fracture data and Bayesian inference, it is possible to improve the precision of the probabilistic fracture prediction of our framework outputs.

4. Future work

We will create a database for crack orientation prediction. Further validation experiments will be carried out. In the near future, we aim to accomplish multiple crack parameter prediction for three dimensional cases. Databases will be created by simulation and validated by multiple samples that are available in the lab. During the course of this project, we plan to extend our newly developed foundations combining finite element simulations with neural network to detect interacting anomalies such as crack with corrosion wall loss and crack in presence of another crack. We will continue to calibrate GTN parameters for various steels of interest. We will create simulation and failure databases for flaws in pipes. For crack-like flaws and corrosion wall-loss flaws, geometric parameters such as crack size, crack location and wall loss depth will be variables in the database. Failure analysis will be performed for the database with a goal to create failure prediction curves/equations. In this project, we plan to implement a probabilistic prediction framework with a possibility of including Bayesian statistics.

References

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